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MOBILE MONEY, REMITTANCES AND NON-MONETARY POVERTY: EVIDENCE FROM RWANDA

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Abstract

This paper uses cross-sectional data from the FinScope 2020 survey in Rwanda to assess the impact of mobile money on non-monetary poverty across three dimensions: nutrition, health and education. Using Instrumental Variable estimation, I find that mobile money use decreases the likelihood of experiencing poverty related to nutrition, but has no impact on accessing health and education. I find that rural farmers at the bottom of the wealth distribution are more likely to receive remittances after a shock, consistent with the explanation of improved risk-sharing via increased remittances, which are primarily used to secure food consumption.

Keywords: Development Economics, Poverty, Financial Inclusion, Mobile Money, Rwanda Risk-Sharing

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1. Introduction

Financial exclusion is widely considered a key impediment to poverty alleviation and growth in many developing countries. For years, high fees, sparsely located branches and complicated registration processes have severely restricted the access of the rural poor population to the most basic financial products, limiting their ability to smooth consumption and insure their incomes (Demirgüc-Kunt et al., 2017). The high cost of extending financial access, paired with other market failures such as high transaction costs, low competition or asymmetric information has long kept the poor financially excluded (Aron, 2018; Karlan, 2016).

Driven by the broad dissemination of mobile phones in the past decade, mobile money emerged as a powerful tool for overcoming these issues and spreading financial services easily and at low cost to the rural poor (Aron, 2018). Mobile money allows users to send, deposit and withdraw funds without bank account ownership, only requiring access to a cell phone and utilizing existing infrastructure in the form of store owners and airtime sellers for cashing in and out (Donovan, 2012). First introduced in Kenya in the late 2000s, the technology quickly gained popularity in eastern Africa, with the number of mobile money accounts now greatly surpassing that of bank accounts in many countries (GSMA, 2021).

The impact of mobile money has been analyzed in different settings, with most studies focusing on the technology's potential to facilitate remittances by lowering the cost of and risk associated with geographically disparate transactions (Suri, 2017). In doing so, many authors have taken a narrow view, focusing mainly on how remittances translate into consumption smoothing. Although recent studies suggest that mobile money can improve selective outcomes related to health and education (Abiona & Koppensteiner, 2020; Jack & Habyarimana 2018), few studies take a holistic stance and examine the extent to which mobile money can alleviate poverty in its multidimensional sense

(Abiona & Koppensteiner, 2020; Batista & Vicente, 2018; N'dri & Kakinaka, 2020). This is particularly true in the case of Rwanda, where to date there is virtually no study linking mobile money to improvements in outcomes related to welfare. Against this backdrop this paper uses a recent and comprehensive data set to examine how mobile money can alleviate poverty in Rwanda along three key dimensions: nutrition, health and education. To connect the results to major findings in the field, the paper then examines how users of the technology benefit from remittances which improve risk-sharing. For this purpose, I employ OLS, IV and Matching methods on recent cross-sectional data from Rwanda.

The rest of the paper is organized as follows: section 2 references the literature and describes the setting, section 3 describes the data and measurement and section 4 introduces the empirical strategy. Section 5 reports and discusses the results and examines risk sharing as an impact mechanism. Section 6 concludes.

2. Literature

In its most basic form, mobile money is a cheap, accessible, safe and easy-to-use means of sending and storing money (Donovan, 2012). Reducing transaction costs and ensuring safety, mobile money has the greatest potential to increase efficiency of transactions across large geographical distances or where the opportunity cost of holding cash is high (Suri, 2017). Because of these properties, widespread use of mobile money can theoretically lead to improvements on many outcomes: through increased and more efficient remittances it could encourage migration, leading to improved distribution of human capital, and improve the allocation of risk and savings across households and firms(Jack & Suri, 2011; Suri, 2017). Through its storage-property, mobile money could increase savings (Suri, 2017) and through the privacy of accounts it could influence bargaining power within the household (Kim, 2021; Suri, 2017).

Different strands of the empirical literature have confirmed the capacity of the technology to induce occupational change (Aggarwal et al., 2020; Batista & Vicente, 2018; Suri & Jack, 2016) as well as its beneficial impact on savings (Bastian et al., 2018; Habyarimana & Jack, 2018; Suri & Jack, 2016) and its potential to boost female empowerment (Aker et al., 2016; Bastian et al., 2018; Riley, 2020; Suri & Jack, 2016).

This research relates to a growing body of empirical research showing how mobile money can beneficially impact outcomes related to consumption and nutrition. Mobile money has been shown to have positive effects on consumption smoothing in different settings (Jack & Suri, 2014; Batista & Vicente, 2018, Abiona & Koppensteiner, 2020). Other studies confirm the technology's capacity to improve household welfare as measured by consumption (Munyegera & Matsumoto, 2016) as well as its beneficial impact on food-security (Murendo & Wollni, 2016) and increased or more diverse expenditures on food (Murendo & Wollni, 2016; Aker et al., 2016).

Examining the impact of mobile money on receiving remittances after an exogenous shock, my paper further relates to a strand of literature documenting increased remittances as an impact mechanism through which mobile money enables these improvements (Abiona & Koppensteiner, 2020; Batista & Vicente, 2018; Jack & Suri, 2014; Munyegera & Matsumoto, 2016; Riley, 2018) Increased remittances have been found to improve risk-sharing and thereby resilience to adverse shocks (Jack & Suri, 2014; Riley, 2018). In Jack & Suri (2014), only mobile money users can prevent a drop in consumption after a shock, a finding which is confirmed by Riley (2018) in Tanzania. In Rwanda, Blumenstock et al. (2016) find that airtime-transfers[1] are used to send funds to those affected by unexpected natural disasters. Gains in financial resilience are documented more recently in Mawejje (2019) who finds mobile money users in Uganda to be less likely to cut back

[1] Airtime transfers preceded mobile money as a means of sending money over distance by means of a phone.

consumption in response to a shock and in Afawubo et al. (2020), who find that mobile money users in Togo appear to be more resilient to weather shocks. Looking at the effects of mobile money use on financial behavior in Tanzania, Ismailov et al. (2019) find that users are less vulnerable to adverse shocks, although they attribute this finding to constant remittances, which can be saved and used in response to a shock. Suri et al. (2021) provide evidence that mobile money loans lower household vulnerability, as users are less likely to forgo expenses in response to a shock. Moreover, my research combines these insights with those from a smaller strand of literature that considers welfare improvements related to health and education: the literature finds that mobile money use can improve health-related outcomes by helping user households to maintain healthcare investment after a rainfall shock (Abiona & Koppensteiner, 2020), and increasing users' propensity to save for health emergencies (Ky et al., 2018). Moreover, mobile money use can improve outcomes related to education in response to a shock by decreasing the extent to which households cut back spending on education (Tabetando & Matsumoto, 2020) and their likelihood to pull their kids out of school (Abiona & Koppensteiner, 2020). In the absence of shocks, the randomized promotion of mobile money savings accounts has been found to increase high school enrolment (Habyarimana & Jack, 2018). In recent work, N'dri & Kakinaka (2020) take a multidimensional perspective by looking at the beneficial effects of mobile money on non-monetary welfare along all three dimensions mentioned above: nutrition, health and education. Using matching methods on FinScope data from Burkina Faso, they find that individuals accessing financial services through mobile money benefit across all three domains (N'dri & Kakinaka, 2020), without, however, shedding light on impact mechanisms. This research builds on their work by examining the impact of mobile money on poverty along the same three dimensions, employing different methods to overcome the endogeneity of mobile money use and further exploring improved resilience to shocks via increased remittances as an impact mechanism.

2.1. Context

The setting of the study is Rwanda, a poor landlocked country in sub-Saharan Africa, where 38% of the population lived below the poverty line in 2017 (NISR, 2018). The country's population is very young and predominantly rural, with the majority of people surviving on subsistence agriculture (NISR, 2018). Currently, the government pursues the target of reaching 100% formal or informal financial inclusion[2] by 2024 (FinScope, 2020). Indeed, the fraction of formally or informally financially included individuals has increased substantially from 48% in 2008 (FinScope 2012) to approximately 93% in 2020 (FinScope, 2020). As in many other East African countries, these developments have been supported by the introduction and fast dissemination of mobile money. Mobile Money was introduced in Rwanda in 2010 by MTN, followed by Tigo in 2011 and Airtel in 2013. Mobile phone penetration even in rural areas is high in Rwanda, with 87% of the population having access to a cell phone (FinScope, 2020). Even though mobile money was formally introduced in Rwanda later than it was in its neighboring countries, its uptake has increased to approximately 60% of the population by 2020 (FinScope 2020).

3. Data & Measurement

3.1.Data

I use cross-sectional data from the 2020 edition of the FinScope consumer survey in Rwanda. FinScope surveys are nationally representative individual-level surveys, conducted by FinMark Trust in cooperation with local governments in different developing countries. The goal of the survey is to obtain reliable, micro data on how a country's citizens manage their financial lives. Along with modules on a person's socioeconomic background, financial capacity, usage of

[2] Individuals are considered informally financially included if they access financial services not through banks but, for instance participate in rotating credit and savings associations (ROSCAs) or have a mobile money account. (FinScope, 2020).

financial services and money management, the survey contains a dedicated section on mobile money and remittance behavior, and a comprehensive section on income shocks that respondents experienced. Data on N = 12,480 individuals were collected in interviews between September and November 2019[3].

3.2.Variables and Measurement

This paper takes a holistic perspective on poverty, considering its multidimensional nature and therefore uses non-monetary poverty indicators. Although monetary measures, such as income, are widely used in the literature, a growing body of research emphasizes the importance of considering non-monetary sources of deprivation to examine poverty (Batana, 2013). Moreover, especially in sub-Saharan Africa, precise estimates of monetary poverty measures are often hard to obtain, because many people lack formal and regular income sources, often relying on subsistence agriculture. Therefore, three non-monetary poverty indicators which are included in the FinScope survey will be used, each capturing deprivation in one of the three key dimensions outlined in the previous section: nutrition, health and education. Poverty in each category is captured by a binary variable, indicating whether a person had to either skip meals, forgo medical expenditure or was unable to send their children to school because they did not have enough money in the past three months.[4] For brevity these categories will be referred to as nutrition, health and education.

The main explanatory variable, mobile money use, equals one if a person indicated that they used mobile money either through their own or someone else's phone in the past 6 months. In a later section of the paper, I examine increased remittances after a shock as an impact mechanism. For

[3] The data are geographically disaggregated at the district level and sampled villages are assigned a numerical code.
[4] Note that in the original data set, the questions correspond to categorical variables with the options "never", "a few times" and "many times", from which dummy indicators were created. These have the benefit of being less ambiguous, since the distinction between a few and many times can be highly subjective. Interpretating the coefficients in the subsequent analysis thus becomes more straight forward.

this purpose, I use a dummy variable indicating if a person received remittances. If respondents indicated that they received the money because they lent it to that person or that the sender was a customer, I did not consider the transfer a remittance. I consider two different types of shocks: those related to health and those related to weather[5]. I created two binary variables capturing whether a respondent reported a health or weather-related income shock in the 12 months preceding the survey. If a person cited illness, death or disability of themselves or a household member, they were classified as having experienced a health shock. The weather shock measure was created considering the fraction of individuals in a village that reported damage or loss of crop or household assets due to drought, flood or fire. The shock was extended to every individual in a given village if more than two people reported it, to address likely underreporting of such shocks, since the survey question only asks respondents to report a shock if it adversely affected their income.

Similar to Riley (2018), I constructed a wealth index using principal component analysis (PCA). The data only contained variables indicating the possession of households' assets and the materials used in the construction of their dwelling, but did not capture the monetary value of these assets, which cannot simply be added up because their relative importance in households' wealth varies. Their importance can be assessed with PCA, where the first component accounts for the largest variance across variables. Based on this component, which is assumed to represent wealth, a weight that indicates its relative importance in constructing the principal component, is assigned to each variable. These factor weights were then used to construct the wealth index. For simplicity in the further analysis, five wealth quantiles were generated based on the resulting wealth distribution and individuals were assigned to one of the quintiles according to their wealth score.

[5]I consider these shocks because they are the most frequently reported and because they can be considered most random, although this is more true for weather than for health shocks. Severe rainfall shocks, such as floods or droughts cannot be predicted and can affect any household. While the occurrence of severe illness or death has a random element, some people might be able to mitigate or prevent them.

3.3.Descriptive Statistics

Table 1: Summary Statistics by Mobile Money Usage Status

Variables	**Users of Mobile Money**		**Non-Users of Mobile Money**	
	Mean	SD	Mean	SD
Individual Characteristics				
Age	39.14	13.19	45.07	18.23
Is female	0.53	0.50	0.66	0.47
Completed primary education	0.52	0.50	0.54	0.50
Completed secondary education	0.28	0.45	0.09	0.29
Is married	0.62	0.49	0.51	0.50
Household Characteristics				
HH size	4.62	1.94	4.23	2.04
HH head is female	0.25	0.43	0.36	0.48
HH lives in urban area	0.60	0.49	0.32	0.47
HH is engaged in farming	0.73	0.45	0.89	0.31
HH travel time to nearest market (percent)				
1 - less than 15 min	*31%*		*14%*	
2 - between 15 and 30 min	*30%*		*20%*	
3 - between 31 and 60 min	*18%*		*24%*	
4 - more than 60 min	*21%*		*43%*	
HH wealth quintile (percent)				
1	*6%*		*38%*	
2	*15%*		*27%*	
3	*21%*		*19%*	
4	*27%*		*11%*	
5	*32%*		*4%*	
Finance & Technology				
Has a bank account	0.35	0.48	0.05	0.22
Saves	0.94	0.23	0.75	0.43
Has access to cellphone	1.00	0.00	0.53	0.50
Received Remittance	0.48	0.50	0.07	0.25
Income Shocks				
Experienced health-related income shock	0.38	0.49	0.42	0.49
Experienced weather-related income shock	0.28	0.45	0.36	0.48
Poverty				
Missed a meal	0.49	0.50	0.80	0.40
Forgone medical treatment	0.34	0.47	0.58	0.49
Unable to send kids to school	0.45	0.50	0.62	0.48
	N = 7,089		N = 5,391	

Table 1 displays a summary of all main variables of interest as well as household and individual level controls. Out of the full sample of 12,480 individuals, 7,089 (56.85%) are active users of

mobile money. On average, a person using mobile money is 39 years of age, 6 years younger than the average non-user. Moreover, users of mobile money are more likely to be male and married. Users are approximately as likely to have completed primary education as non-users, though substantially more users have also completed secondary education (8% vs. 29%). The average household size in the sample is between 4 and 5 people, with non-user households being slightly larger than user households. A minority of households is female-headed, although that fraction is larger among non-user households than among user households. Mobile money users are substantially more likely to live in urban areas and less likely to be engaged in farming as their primary activity. Unsurprisingly, user households thus also display a shorter average travel time to the closest market. Notably, mobile money users are on average wealthier than non-users: a disproportionate share of non-users can be found in the top quintiles, while for users, the opposite is true. For the middle quintile, the distribution is even with about 20% of users and non-users falling into this category.

Further, users of mobile money in the sample exhibit a greater degree of financial inclusion: 35% have a bank account, and 94% save. Unsurprisingly, every respondent in this subsample has access to a cellphone. Contrarily, only 5% of non-users have a bank account; 75% save and 53% have access to a cellphone. Almost half of all mobile money users received a remittance in the 6 months prior to the survey, compared to only 7% of non-users. Users are also slightly less likely to report having experienced a health or weather-related income shock[6]. Prior to the survey, 49% of users missed a meal due to lack of food, compared to 80% of non-users. Users are also less likely to indicate being unable to pay for medical treatment or to send their kids to school. Only 34% of

[6] If shocks do not occur purely randomly, this might be a concern. I address this issue in a later section of the paper and explicitly confirm that these differences are not statistically significant, in particular not when considering the reporting of shocks within a wealth quintile.

users, compared to 58% of non-users had to forgo medical treatment and 45% of users were unable to send their kids to school, which is true for 62% of non-users.

4. Empirical Strategy

4.1.Empirical Specification

This paper focuses on estimating the impact of mobile money on non-monetary poverty. Benefitting from faster and safer transactions and inter alia an increased ease of receiving remittances, users are expected to have higher disposable incomes, which translates into lower chances of missing meals, having to forgo medical treatment and being unable to send their kids to school. I therefore estimate the following specification:

$$y_i = \beta_0 + \beta_{mm} mobilemoney_i + \gamma X_i + \varepsilon_i \quad (1)$$

In equation 1, y_i represents one of the three poverty outcomes of interest, for example the probability that a person missed a meal because they did not have food. $mobilemoney_i$ is a binary indicator that equals one if the person uses mobile money. X_i is a vector of controls, including other household and individual-level variables that might affect whether an individual experienced poverty in the corresponding outcome categories. This includes, for example, important socio-economic characteristics such as age, education and wealth, as well as financial inclusion indicators, such as whether a person has a bank account[7]. The full set of controls is described in Table 1. Moreover, the vector of controls includes the distance to the nearest hospital or school when estimating the impact on the probability of forgoing medical treatment and that of being unable to send your kids to school, respectively. ε_i is a random error term. The coefficient of interest, β_{mm} captures the impact of using mobile money on the poverty outcome of interest. If

[7] These controls are commonly used in the related literature (Munyegera & Matsumoto, 2016; Riley, 2018; Tabetando & Matsumoto, 2020).The full set of controls is displayed in Table 1 and includes all individual and household characteristics as well as all financial and technological indicators except for whether that person received a remittance.

using mobile money is associated with a lower likelihood of experiencing poverty in a specific category, β_{mm} will be negative and represent the percentage-point reduction in the chance of experiencing non-monetary poverty that is caused by using mobile money.

4.2.Identification Strategy

The dependent variable of interest is a binary indicator, which can only take the value zero or one. Therefore, the model can also be thought of as estimating a conditional probability of Y being equal to one, or true. Probit or logit models are often used for estimating these type of equations, because they restrict the value of Y to the range between 0 and 1. In development economics and when studying related questions, OLS regression is however, still a frequently used technique to estimate effects on binary dependent variables.[8] The model then becomes equivalent to a linear probability model (LPM), which implies that the change in the probability of experiencing poverty in one of the three categories is linear, and thus the same for any value of the independent variable. The reasons why these models are commonly used are first, that this is usually a defensible hypothesis. Second, LPMs are typically employed because they are easier to interpret and implement: the coefficient estimates can be interpreted without needing to derive marginal effects as a second step and thus also have the advantage of being more transparent. Considering that coefficient estimates are often similar between LPMs and probit or logit models, and after confirming that marginal effects from probit regressions are similar to OLS estimates[9], I thus estimate equation (1) by OLS.

For the parameter β_{mm} to be estimated consistently and without bias, the error term ε_i must be uncorrelated with $mobilemoney_i$ conditional on the set of control variables, that is mobile money

[8] See, for instance, Abiona & Koppensteiner (2020), Batista & Vicente (2018), Jack & Suri (2014), Murendo & Wollni (2016) for examples of related work estimating binary dependent outcome variables with OLS.
[9] The results of estimating the impact of mobile money through probit estimation on each category of non-monetary poverty can be found in Appendix 3.

use must be exogenous. First, concerns that this might not be the case arise from self-selection into using the technology and if access to mobile money is not random[10]. Whether someone uses mobile money is not determined at random: individuals select into it, based on observable and unobservable characteristics, resulting in systematic differences between users and non-users. Statistics reported in Table 1 indicate that the use of mobile money correlates with a variety of observable characteristics and their relevance in determining mobile money use was confirmed by running a separate regression, the results of which can be found in Appendix *2*. These factors can be controlled for by including them in the regression. However, if people select into mobile money based on unobservable characteristics, which might also affect their likelihood of experiencing poverty in any of the three categories, the estimate for β_{mm} will be biased and inconsistent, because the exogeneity assumption will be violated and β_{mm} may merely capture a spurious correlation. Conditional on being time-invariant, individual-specific unobservable characteristics can be fully controlled for in fixed effects specifications. This, however, is only possible if the data have a time-series component. Since the data used in this analysis are cross-sectional, fixed effects estimation cannot be used and OLS is the only option for estimating equation (1). Moreover, since only one point in time is observed, issues of simultaneity and reverse causality cannot be resolved and we cannot know in which direction causality flows. In light of these issues, OLS estimates will be interpreted with caution.

I address these concerns with instrumental variable regression (IV). The endogeneity issue can be resolved if there is an instrument Z, which is correlated with the endogenous variable and which is correlated with the outcome variable only through its effect on the endogenous variable. An

[10] The latter concern can be alleviated when considering the fast and simultaneous rollout of mobile money agents in Rwanda (International finance corporation, 2012) resulting in broad access to mobile money in all parts of the country (FinScope, 2020), and the fact that agents are pre-existing shop-owners or airtime sellers. I address this concern in more detail when looking at distance to the nearest agent as an IV for mobile money use.

instrument for mobile money commonly used in the literature (Abiona & Koppensteiner, 2020; Jack & Suri, 2014; Riley, 2018; Tabetando & Matsumoto, 2020) is distance to the nearest mobile money agent. For β_{mm} to be identified without bias and consistently, distance to the nearest mobile money agent must predict mobile money use (Instrument relevance), while impacting an individual's likelihood of experiencing non-monetary poverty through no other channel than this (Instrument exogeneity). In the data, more than 25% of mobile money users cite proximity and availability as the main reason for using the technology, indicating that agent-distance matters for mobile money use. It therefore appears plausible that greater distance to the nearest agent might discourage mobile money use. Concerns regarding the instrument's exogeneity arise if there is a direct relation between the distance to the nearest agent and an individual's poverty. The standard assumption in the literature is that, in light of the fast and simultaneous roll-out of mobile money and the agent network, as well as the nature of the agent business, this seems unlikely: owners of previously existing shops and sellers of airtime are the vast majority of those who went on to become agents, which means that existing infrastructure was the one primarily employed in mobile money roll-out. Agents further do not require a minimum number of customers for the business to be viable, since they earn a commission per transaction, removing an important barrier in poorer or more rural areas. In fact, within less than two years of introduction, the number of agents in Rwanda had increased to 1,500, clearly exceeding the number of ATMS and bank branches in the country at that time (147 and 223, respectively) (International Finance Corporation, 2012).

5. Results & Discussion

5.1.OLS Estimation

This section reports and discusses the results. First, I examine the results of estimating equation (1) by OLS, before discussing heterogeneous effects. Then, I report and discuss results of estimating

equation (1) with IV, using distance to the nearest mobile money agent as an IV for mobile money usage. Finally, improved risk-sharing as an impact-mechanism is explored.

Table 2: The Impact of Mobile Money on Non-Monetary Welfare (OLS Results)

	Nutrition - *(Had to skip meals dummy)*	Health - *(Had to forgo medical treatment dummy)*	Education - *(Unable to send kids to school dummy)*
	(1)	(2)	(3)
Uses mobile money	-0.0635***	-0.0339***	-0.0305**
	(0.0109)	(0.0128)	(0.0124)
N	12,411	12,411	12,411
R^2	0.27	0.15	0.08

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column represents a different regression. Each regression contained the full set of controls mentioned in section 3. Coefficient estimates of the control variables are not reported for clarity. Standard errors clustered at the villages level.

Table 2 reports the coefficients on mobile money obtained from estimating equation (1) by OLS. The coefficient of mobile money reported in column 1 is -0.0635 and it is statistically significant at a 99% level. Thus, controlling for a variety of individual- and household-characteristics, mobile money use is associated with an approximately 6 percentage-points lower chance of having missed meals due to poverty. The coefficient of mobile money reported in column 2 represents the association between mobile money use and the likelihood of recently having missed medical treatment conditional on the controls. Mobile money use is associated with a 3.39 percentage-points lower chance of experiencing poverty in this regard. Again, the coefficient is statistically significant at the 99% level. Similar results are reported in column 3: the coefficient of mobile money is -0.0305 and its statistical significance is high (95%), indicating that mobile money use is further associated with an approximately 3 percentage point lowered chance of being unable to afford sending your kids to school. As predicted, β_{mm} is negative in all three columns. Overall, this implies that mobile money use is associated with a decreased chance of experiencing poverty across all three categories. The effects are highly statistically significant in all cases and are

strongest and largest with respect to nutrition. Overall, these findings are in line with what was expected based on the literature, in particular with N'dri & Kakinaka (2020).

5.1.1. Robustness of OLS Results

To explore heterogeneous effects, I ran regressions on different subsets of the population. Because I am particularly interested in exploring the potential of mobile money for financial inclusion and ultimately poverty alleviation, a concern is whether the results hold for the poorest. A concern might, for instance, be that the results are entirely driven by the wealthier population, which can both easily afford cell phones and use mobile money, and is less likely to experience poverty. The results are robust to restricting the sample only to individuals with access to a cell phone, to those without a bank account and to the rural or farming population. Most importantly, when looking at each wealth quintile separately, coefficients increase and become more significant the lower the wealth quintile. Results of these regressions are reported in Appendix 4 and Appendix 5 .

As a first step to alleviate endogeneity concerns, I also estimated the impact of mobile money in each of the three categories by propensity score matching (PSM). The results and details of this estimation are reported in Appendix 6. In doing so, the coefficient on mobile money with regards to nutrition increased slightly in absolute magnitude and remained highly statistically significant. The coefficient on health remains stable, while that on education turned insignificant. Together, these results point towards an underestimation of the effect of mobile money usage on the probability of having missed meals and an overestimation of the impact that mobile money usage on the probability of being unable to send your children to school. When interpreting these results, it is however important to keep in mind that individuals can only be matched on observable characteristics, so matching methods may not fully eliminate endogeneity issues.

As a final robustness check, I employed inverse probability weighting (IPW) to establish represen-

tativeness by account for the sampling probability of observations and remove any bias which may have resulted from using an unweighted estimator. The results are reported in Appendix 6 and are similar, if not almost equal to the results reported in Table 2.

5.2.IV Estimation

Table 3: The Impact of Mobile Money on non-Monetary Poverty (IV Results)

	Nutrition - *(Had to skip meals dummy)*	Health - *(Had to forgo medical treatment dummy)*	Education - *(Unable to send kids to school dummy)*
	(1)	(2)	(3)
Uses mobile money	-0.3439*	-0.0116	0.1594
	(0.1865)	(0.2123)	(0.2321)
N	12,411	12,411	12,411
R^2	0.23	0.15	0.06
Cragg-Donald Wald F-Statistic	38.7	38.69	34.26
Underidentification Test $\chi^2(1)$ (p-Value)	0.00	0.00	0.00
Stock-Wright LM S Statistic	3.62	0.00	0.48

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each regression contained the full set of controls mentioned in section 3. Coefficient estimates of the control variables are not reported for clarity. Only Second-Stage results are reported. Standard errors clustered at the village level.

Results reported in the previous part assumed that mobile money use was allocated randomly to individuals conditional on observables, an assumption which likely does not hold, as pointed out in section 4. To address this issue, I estimated the specification of interest by IV. Table 3 reports the second stage results and most relevant corresponding test statistics.

Using IV, the coefficients and standard errors become large and significance decreases. This might raise questions regarding the instrument's strength. However, based on the extremely low p-value of the Underidentification test reported in Table 3, I fail to reject the null hypothesis that the instrument has no or only a weak impact on the endogenous variable, on the 1% level. This is further supported by the Cragg-Donald-Wald F-Statistics reported in Table 3, which are well above the Stock-Yogo critical values. On these grounds, I conclude that the instrument is strong and

proceed with the interpretation of the coefficients. After instrumenting mobile money usage with distance to the nearest agent, the coefficients of mobile money on non-monetary poverty in the dimensions health and education become insignificant. The coefficient of nutrition, however, increases drastically compared to the OLS-estimation, to -0.3439, although the standard error is large (-0.1865) and the coefficient is only statistically significant on a 10% level. These results indicate that using mobile money causes a drop of approximately 34 percentage points in a person's likelihood to miss meals due to lack of money. They further suggest that using mobile money does not cause any differences in someone's likelihood of being unable to afford medical treatment or sending their kids to school, although the coefficient of mobile money on the latter outcome increased in magnitude and turned positive[11]. Overall, OLS underestimated the effect that mobile money usage has on the probability of experiencing poverty in the first category (nutrition) and overestimated the impact that using the technology has on the probability of experiencing poverty in the latter two categories, although the effect on education is ambiguous, given the relatively large and positive, yet statistically insignificant coefficient in this case. That is, OLS estimates are biased upwards regarding the first outcome and biased downwards when estimating the impact of mobile money on the latter two outcomes.

The fact that mobile money seems to improve nutrition, but not health and education might be explained by the different nature of the three outcomes considered. Out of the three, nutrition is by far the most basic need and missing a meal thus the most severe measure of poverty. Whereas the only reason not to eat is an acute lack of food or money, the decision to forgo medical treatment or not to send your children to school may be more complex and more dependent on unobservable

[11] Its standard errors is, however, large and the effect is statistically insignificant, which is why I cannot reject the null hypothesis that mobile money usage has no impact on the likelihood of being unable to send your children to school and the coefficient cannot be interpreted as measuring any impact in the following.

characteristics, such as a person's attitudes or information network. As those using mobile money are on average wealthier, more educated and live closer to infrastructure, it is likely that before accounting for endogeneity, the coefficients of mobile money on the latter two outcomes captured biases resulting from these systematic differences. Being more educated, user households might for instance place greater value on both health and education, increasing their reluctance to forgo medical treatment or not send their kids to school.

How can the sizeable effect of mobile money on nutrition be explained? The literature points towards different impact mechanisms, with increased remittances being the most important channel through which mobile money could affect this outcome. Remittances might explain the beneficial impact of mobile money on nutrition if they primarily help the most vulnerable people which proceed to spend the additional income on food. Because mobile money allows smaller amounts to be sent more frequently and quickly in the case of an adverse shock where securing food intake might become a priority, users could benefit especially through a decreased likelihood of having to miss meals. The data support this theory: more than 50% of those who received a remittance via mobile money indicated that they spent it on food or clothes, the share increasing the lower the recipient's wealth status. Mobile money users are also more likely to send remittances frequently and regularly, and in smaller amounts: while the average remittance sent via mobile money amounts to about 28.5 USD, the average remittance sent via different means amounts to about 133.8 USD.[12] On these grounds, the next section examines the extent to which mobile money use facilitates remittances in case of an adverse income shock.

5.3.Mechanisms

[12] Survey data is in Rwandan francs and was converted into USD using the average exchange rate of 2019, when the survey was conducted. Descriptives are displayed in Appendix 14 and Appendix 15.

5.3.1. Empirical Specification

A mechanism linking mobile money usage to increased welfare confirmed in different settings (Batista & Vicente, 2018; Jack & Suri, 2014; Riley, 2018) is improved risk-sharing via remittances. Households hit by a shock, for instance a flood destroying crop, usually have no option but to cut back consumption in response to the sudden decrease in disposable income. In these cases, mobile money can moderate the shock's adverse impact because the technology allows users to access a wider support network from which they can receive quick financial help in the form of remittances. If mobile money alleviates poverty through this channel, mobile money users that report having experienced an adverse income shock will be more likely to have received a remittance. Because those receiving remittances via mobile money are expected to be the most vulnerable to missing meals, the analysis will focus on mobile money's potential to facilitate remittances and not on the impact of remittances on the likelihood of missing a meal, as these results may be misleading. Similar to Batista & Vicente (2018), Jack & Suri (2014) and Riley (2018) I therefore write the following specification:

$$Rem_i = \beta_{MM} mobilemoney_i + \beta_{MMS} mobilemoney_i x\ Shock_i + \beta_S Shock_i + \gamma X_i + \varepsilon_i \qquad (2)$$

In equation (2), the dependent variable is a dummy indicator, capturing if a person received a remittance in the past 6 months. As in equation (1), $mobilemoney_i$ is a binary indicator capturing if a person is an active user of mobile money, X_i is a vector of controls,[13] and ε_i is a random error term. $Shock_i$ is a dummy variable that equals one if the respondent reported having experienced an income shock in the 12 months prior to the survey. As illustrated in section 3, I consider two different types of income shocks separately: those related to health and those related to weather. The main parameter of interest, β_{MMS}, captures the differential impact of mobile money use on the

[13] The vector of controls is the same as in equation (1).

probability of receiving remittances in case the person experienced an income shock. If people benefit from using mobile money through improved risk sharing, they will be more likely to have received a remittance if they experienced an adverse income shock and β_{MMS} will be positive.

5.3.2. Identification Strategy

As in the previous section, equation 2 is estimated by OLS. For β_{MMS} to be estimated without bias and consistently, shocks must be distributed randomly across people. While, however, the occurrence of shocks is per definition random,[14] the vulnerability of someone's income to them likely is not. Since the corresponding survey question asks respondents for events that negatively affected their income, the shock measure might be subject to underreporting by people who are less vulnerable to a certain shock, for instance because they are wealthier. In this case, the shock-measure will be correlated with any factors along which a person's vulnerability to shocks varies. I explore the extent to which this is an issue for each of the two by regressing each shock-indicator on the vector of controls[15]. Indeed, wealth is an important predictor of both shocks. To eliminate this bias, I looked at each wealth quintile separately, to determine if a shocks appear more random *within* wealth quintiles, where people's vulnerability to them is likely similar. For health-related shocks, this is the case, as within quintiles, only age is correlated with the shock indicator, although its coefficient is very low. All models further exhibit very low R-squared statistics, indicating that none of the variables substantially explains the incidence of the shock. Therefore, it is plausible to consider the health shock exogenous within a wealth quintile. Looking at weather shocks, in

[14] Both types of shocks which are considered have a random element: shocks relating to health, such as severe illness, death and disability are unpredictable events which can affect anyone. They can however, be mitigated, and are therefore not entirely random. Shocks related to weather, such as droughts or floods, are too, unpredictable and can occur anywhere. Compared to the health shock, they are harder to prevent and are not subject to the same concerns regarding their randomness. Nevertheless, because I am dealing with self-reported data, results will be interpreted with caution.

[15] Results from these regressions are reported in Appendix 7, Appendix 8, Appendix 9 and Appendix 10

addition to less wealthy people, farmers and rural people are more likely to report having experienced this type of shock. This is not surprising, because weather shocks affect people's income adversely mainly by destroying crop, so rural farmers are more vulnerable to these events. Looking at rural farmers only, I see that within each wealth quintile of this subset of the population none of the relevant variables is correlated with the shock, other than what would be expected by chance and all models exhibit very low explanatory power. Knowing that weather shocks are per se random, this suggests that they can be considered exogenous among this subset of the population. Thus, equation (2) was estimated separately for each wealth quintile and for the subset of rural farmers for each of the two shocks.

5.3.3. Results and Discussion

Table 4 reports results from estimating equation (2) for the different subsamples of the population highlighted in the previous section[16]. For each subsample, columns (a) report the coefficient estimates of the regressions considering health shocks, while columns (b) report the coefficient estimates of the regressions considering weather shocks. Based on the elaborations in the previous section, causal inference regarding the parameter of interest β_{MMS} can only be made within wealth quintiles and, when looking at weather shocks, for the rural/farming population.

The coefficient of mobile money is always large and highly statistically significant. This is true for both types of shocks across all wealth quintiles. Thus, using mobile money in the absence of shocks is associated with a large increase in the probability of receiving remittances: depending on the subsample people using mobile money are between 25 and 40 percentage points more likely to

[16] Results of estimating equation 2 for both types of shocks and all subsets of the equation are displayed in Appendix 11, Appendix 12, Appendix 13.

have received a remittance. This is not surprising, since there is a direct link between both variables, as most remittances are sent via mobile money (FinScope, 2020).

Table 4: The Impact of Mobile Money and Shocks on Receiving Remittances (OLS Results)

	Dependent variable: Received remittances dummy					
	Full Sample		Rural Farmers		Rural Farmers – 1st Wealth Quintile	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Mobile Money	0.3340***	0.3342***	0.3062***	0.3049***	0.2532***	0.2502***
	(0.0108)	(0.0111)	(0.0148)	(0.0148)	(0.0367)	(0.0349)
Mobile Money x Healthshock	0.0199		0.0376*		0.1097**	
	(0.0142)		(0.0212)		(0.0558)	
Healthshock	0.0198***		0.0097		-0.0022	
	(0.0071)		(0.0082)		(-0.0108)	
Mobile Money x Weathershock		0.0238		0.0414*		0.1214**
		(0.0169)		(0.0233)		(0.0538)
Weathershock		0.0155**		0.0131		0.0079
		(0.0076)		(0.0087)		(0.0109)
N	12,411	12,411	6,070	6,070	1,778	1,778
R^2	0.22	0.22	0.20	0.20	0.20	0.20

Robust standard errors clustered at the village level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each column reports the results of a separate regression. Columns a and b refer to the regression of health shock and the weather shock, respectively. These regressions were run on different subsets of the population, as described in the respective headers. Each regression included the full vector of control variables detailed in section 4. Coefficient estimates on control variables are not reported for clarity.

For both weather and health shocks, the coefficient on the interaction term between shocks and mobile money is insignificant on the aggregate level. I make the same observation when estimating equation (2) for each quintile separately, as warranted by the non-random distribution of the shock. Looking at rural farmers only, for both shocks, there is a significant positive effect of the interaction term on the aggregate level, with the coefficients amounting to 0.0376 and 0.0414 in case of a health and weather shock respectively. A closer look reveals that the effect observed on the aggregate level is entirely driven by the people in the bottom quintile of the wealth distribution. Rural farmers that use mobile money are almost 11 percentage points more likely to have received a remittance if they use mobile money after a health shock, and about 12 percentage points more

likely to have received a remittance after a weather shock.

In summary, I find evidence for improved risk-sharing through increased remittances among rural farmers in the bottom quintile of the wealth distribution, with shocks raising the likelihood of mobile money users receiving remittances by an additional 11 – 12 percentage points, depending on the type of shock. I find no such effect at the aggregate level and among wealthier individuals, although it is possible that part of this is due to the non-randomness of shocks in different subsets of the population. In general, the self-reported shock measure may still be biased, so it is important to confirm these findings using actual weather data to eliminate this source of concern. The findings are broadly in line with the literature (Batista & Vicente, 2018; Jack & Suri, 2014; Riley, 2018), although previous research did not consider heterogeneous effects by wealth status. The findings contradict Blumenstock et al. (2016), who find that wealthy individuals are more likely to receive airtime transfers. Considering that the authors use data from 2009, when mobile money was not formally introduced, my results could, however, be explained by the increasing dissemination of mobile money across a more diverse and poorer set of the population (which makes my setting difficult to compare to one where mobile money was in its infancy). These findings thus highlight the importance of reassessing the impact of mobile money as a larger share of the population has adopted it and has gained experience using it. Because I find that it is the poorest and most vulnerable who benefit in case of a shock, and because remittances are mainly spent on consumption of food or buying clothes, it is important not to overstate the poverty alleviating impact of the technology. Mobile money appears to alleviate the most severe forms of deprivation via increased remittances in the case of shocks, but to make individuals benefit across the scale, more targeted interventions and financial innovation may be needed. Moreover, this paper only assessed remittances as an impact mechanism, yet mobile money might lead to improved livelihoods through other channels, such as improved savings (Habyarimana & Jack, 2018) or

female empowerment (Aker et al., 2016). In light of recent work, such as Ismailov et al. (2019), future research should explore the relative importance of different channels through which mobile money can improve welfare. Nevertheless, the results underscore the validity of current efforts to enable international remittances into mobile money wallets and interoperability (GSMA, 2021).

6. Conclusion

This paper examined the impact of mobile money use on multidimensional poverty using FinScope 2020 survey data from Rwanda. Using Instrumental-Variables Regression, I found that mobile money use caused a drop in the likelihood of having to skip meals by about 34 percentage points, while it was not associated with differences in the probability of being unable to afford medical treatment or sending your kids to school. These differences can potentially be explained by remittances sent to the most vulnerable part of the population in case of an adverse income shock, to ensure food security. Exploring this, I find evidence that rural farmers in the bottom quintile of the wealth distribution are precisely the ones for whom using mobile money increases the likelihood of receiving remittances after a shock. The results confirm the role mobile money can play in poverty alleviation by facilitating remittances and confirm its importance among the subset of the population that is most vulnerable. However, they also indicate that mobile money usage alone may not lead to broader welfare gains, as some research seems to suggest (N'dri & Kakinaka, 2020), and that more sophisticated tools, such savings products built on the rails of the technology, may be necessary to realize benefits across a broader scale. A limitation of the study is its cross-sectional nature. Ideally, future research should take a similarly holistic perspective in a multi-year setting, to obtain a more nuanced understanding of the underlying dynamics. Additionally, future work should assess the relative importance of improved risk-sharing as an impact mechanism compared to other channels such as improved savings.

Bibliography

Abiona, Olukorede, and Martin Foureaux Koppensteiner. 2020. "Financial inclusion, shocks, and poverty: Evidence from the expansion of mobile money in tanzania." *Journal of Human Resources*. AHEAD-OF-PRINT: 1018-9796.

Afawubo, Komivi, Mawuli K. Couchoro, Messan Agbaglah, and Tchapo Gbandi. 2020. "Mobile money adoption and households' vulnerability to shocks: Evidence from Togo." *Applied Economics* 52 (10): 1141-1162.

Aggarwal, Shilpa, Valentina Brailovskaya, and Jonathan Robinson. 2020. "Cashing in (and out): Experimental evidence on the effects of mobile money in Malawi." *AEA Papers and Proceedings* 110: 599-604.

Aker, Jenny C., Rachid Boumnijel, Amanda McClelland, and Niall Tierney. 2016. "Payment mechanisms and antipoverty programs: Evidence from a mobil8e money cash transfer experiment in Niger." *Economic Development and Cultural Change* 65 (1): 1-37.

Aron, Janine. 2018. "Mobile money and the economy: a review of the evidence." *The World Bank Research Observer* 33 (2): 135-188.

Bastian, Gautam, Iacopo Bianchi, Markus Goldstein, and Joao Montalvao. 2018. "Short-term impacts of improved access to mobile savings, with and without business training: Experimental evidence from Tanzania." Center for global development working paper 476 (March):1–24.

Batana, Yélé Maweki. 2013. "Multidimensional measurement of poverty among women in Sub-Saharan Africa." *Social Indicators Research* 112 (2): 337-362.

Batista, C., & Vicente, P. C. 2018. “Is Mobile Money Changing Rural Africa? Evidence from a Field Experiment.” NOVAFRICA Working Paper Series 1805.

Blumenstock, Joshua E., Nathan Eagle, and Marcel Fafchamps. 2016. "Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters." *Journal of Development Economic*s 120 (C): 157-181.

Demirgüç-Kunt, Asli, and Dorothe Singer. 2017. "Financial inclusion and inclusive growth: A review of recent empirical evidence." World Bank Policy Research Working Paper 8040.

Donovan, Kevin. 2012. "Mobile money for financial inclusion*." Information and Communications for development* 61 (1): 61-73.

FinScope. 2012. "Financial Inclusion in Rwanda 2008-2012."

FinScope. 2020. "Financial Inclusion Rwanda 2020."

GSMA. 2021. "State of the Industry Report on Mobile Money 2021."

International Finance Corporation. 2012. "IFC Mobile Money Scoping Country Report: Rwanda."

Ismailov, Askar, Albert Benson Kimaro, and Hisahiro Naito. 2019. "The effect of mobile money usage on borrowing, saving, and receiving remittances: Evidence from Tanzania." Tsukuba Economics Working Papers 2019-002.

Jack, William, and James Habyarimana. 2018. "High hopes: Experimental evidence on saving and the transition to high school in Kenya." Georgetown University, mimeograph.

Jack, William, and Tavneet Suri. 2011. “Mobile money: The economics of M-PESA.” NBER Working Paper 16721.

Jack, William, and Tavneet Suri. 2014. "Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution." *American Economic Review* 104 (1): 183-223.

Karlan, Dean, Jake Kendall, Rebecca Mann, Rohini Pande, Tavneet Suri, and Jonathan Zinman. 2016. “Research and impacts of digital financial services.” NBER Working Paper 22633.

Kim, Kyungha. 2021. "Assessing the impact of mobile money on improving the financial inclusion of Nairobi women." *Journal of Gender Studies.* AHEAD-OF-PRINT. 1-17.

Ky, Serge, Clovis Rugemintwari, and Alain Sauviat. 2018. "Does mobile money affect saving behaviour? Evidence from a developing country." *Journal of African Economies* 27 (3): 285-320.

Mawejje, Joseph. 2019. "Financial inclusion, shocks and coping strategies: survey evidence from Uganda*." African Journal of Economic and Management Studies*. https://doi.org/10.1108/AJEMS-10-2018-0325.

Munyegera, Ggombe Kasim, and Tomoya Matsumoto. 2016. "Mobile money, remittances, and household welfare: Panel evidence from rural Uganda." *World Development* 79 (C): 127-137.

Murendo, Conrad, and Meike Wollni. 2016. “Mobile money and household food security in Uganda.” Global Food Discussion Papers 76.

National Institute of Statistics of Rwanda (NISR). 2018. "EICV5 Main Indicators Report"

N'dri, Lasme Mathieu, and Makoto Kakinaka. 2020. "Financial inclusion, mobile money, and individual welfare: The case of Burkina Faso." *Telecommunications Policy* 44 (3).

Riley, Emma. 2018. "Mobile money and risk sharing against village shocks." *Journal of Development Economics* 135: 43-58.

Riley, Emma. 2020. "Resisting social pressure in the household using mobile money: Experimental evidence on microenterprise investment in Uganda." University of Oxford, 25.

Suri, Tavneet. 2017. "Mobile money." *Annual Review of Economics* 9: 497-520.

Suri, Taveet, Prashant Bharadwaj and William Jack. 2021. Fintech and household resilience to shocks: Evidence from digital loans in Kenya. *Journal of Development Economics* 153.

Suri, Tavneet, and William Jack. 2016. "The long-run poverty and gender impacts of mobile money." *Science* 354 (6371): 1288-1292.

Tabetando, Rayner, and Tomoya Matsumoto. 2020. "Mobile money, risk sharing, and educational investment: Panel evidence from rural Uganda." *Review of Development Economics* 24 (1): 84-105.

Appendix 1: Overview Variable Construction

Variable	Description	Corresponding Survey Question(s)
age	Continuous variable indicating age in years	B1
female	Binary variable that equals 1 if respondent is female	C3
primary education	Binary variable that equals 1 if respondent completed primary education	C4A
secondary education	Binary variable that equals 1 if repsondent completed secondary education	C4A
married	Binary varianle that equals 1 if respondent is married	C4B
hhsize	Count variable indicating the number of people in respondent's household	C0
femaleheaded	Binary variable that equals 1 if respondent's head of household is female	C1B
urban	Binary variable that equals 1 if respondent lives in urban area	A3
farming	Binary variable that equals 1 if repsondent's household is mainly involved in farming	M1
timetomarket	Categorical variable capturing how long it takes repsondent to get to the nearest market in 15 min intervals	D1B1
quintile	Catgorical variable indicating repsondent's household's wealth-quintile, according to a wealth index computed with principal component analysis based on key household assets and dwelling-characteristics (people per room, formal land ownership, owning more than one property, sharing a toilet, type of toilet, materials used for roof, floor and walls of dwelling, main source of lightning, electricity and drinking water, productive & non-productive household assets, and access to technology)	C6B, C6C, C7D, C7E, C10A, C9A1, C9A2, C9A3, C9B, C10B, C11A, C11B, C12_1 - C12_16, C13A, C14B1 - C14B4
bankaccount	Binary variable that equals 1 if respondent has a bank account	K1_2_1
saving	Binary variable that equals 1 if respondent indicated saving in some form	L1A
cellphone	Binary variable that equals 1 if respondent has access to a cellphone, either through ownership or through using that of someone else	C14B1, FM2, FM3
mobilemoney	Binary variable that equals 1 if respondent currently uses mobile money, either through their own account or through someone else's	FM4
distance_agent	Categorical variable capturing the distance of a person to the nearest mobile money agent. If a respondent didn't know the distance, they were assigned the average distance people living in the same village reported.	D1B14
remittances	Binary variable that equals 1 if respondent received a remittance in the last 6 months and this remittance was sent by family member, that person's spouse or a friend. Business-related transmissions (such as loan-repayments or payments by business partners) were excluded.	J3A, J4A
frequency	Categorical variable capturing the frequency and regularity with which respondent receives remittances. (1 = weekly, 2 = biweekly, 3 = monthly, 4 = seasonally, 5 = annually, 6 = irregularly / occasionally)	J4C

Variable	Description	Corresponding Survey Question(s)
poverty_ education	Binary variable that equals 1 if respondent's household had to forgo medical treatment at least once in the past 3 months because of lack of money	C5B
poverty_health	Binary variable that equals 1 if respondent's household could not send kids to school at least once in the past 3 months because of lack of money	C5D
weathershock	Binary varibale that equals 1 if at least two people in respondent's village indicate having experienced an adverse income shock because of flood, fire or draught destroyed houeshold goods or crop.	I1A07, I1A08
healthshock	Binary variable thatr equals 1 if respondent indicates having experienced an adverse income shock due to serious illness or death of a household member, or due to disability.	I1A02, I1A03, I1A11

Appendix 2: Determinants of Mobile Money, Marginal Effects from Probit Estimation

	Uses mobile money Dummy
	(1)
Age	-0.0025***
	(8.25)
Is female	-0.0751***
	(8.65)
Completed primary education	0.0635***
	(6.2)
Completed secondary education	0.119***
	(9.43)
Is married	0.0445***
	(4.21)
HH size	-0.003
	(1.56)
HH head is female	0.0592***
	(4.74)
HH lives in urban area	0.010
	(0.91)
HH is engaged in farming	-0.0333*
	(2.34)
HH wealth quintile	0.0808***
	(20.75)
Travel time to nearest market	-0.0219***
	(4.56)
Saves	0.173***
	(13.33)
Has access to cellphone	
Owns bank account	0.155***
	(12.99)
N	9927
R^2	

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 3: Results from Estimation Equation (1) with Probit, Marginal Effects

	Nutrition	Health	Education
	(1)	(2)	(3)
Uses mobile money	-0.0580***	-0.0301*	-0.0293*
	(5.51)	(2.55)	(2.42)
Age	-0.000193	0.000640*	0.00188***
	(0.66)	(2.13)	(5.82)
Is female	0.00707	0.00132	0.0038
	(0.84)	(0.14)	(0.4)
Completed primary education	0.0231*	0.00748	0.0235*
	(2.42)	(0.7)	(2.01)
Completed secondary education	-0.0182	-0.0410**	0.0326*
	(1.48)	(2.92)	(2.3)
Is married	0.0124	-0.0326**	-0.0845***
	(1.23)	(2.71)	(7.46)
HH size	0.0165***	0.0183***	0.0179***
	(7.89)	(8.34)	(7.05)
HH head is female	0.0535***	0.0272*	0.0379**
	(4.54)	(2)	(2.85)
HH lives in urban area	0.0378**	0.00514	0.00917
	(3.11)	(0.36)	(0.66)
HH is engaged in farming	0.00965	-0.00484	0.00471
	(0.79)	(0.35)	(0.33)
HH wealth quintile	-0.126***	-0.0868***	-0.0590***
	(30.75)	(18.54)	(12.42)
Travel time to nearest market	0.0043	0.00125	-0.00878
	(0.89)	(0.22)	(1.51)
Travel time to nearest health facility		0.0216***	
		(3.92)	
Travel time to nearest school			0.0236***
			(4.08)
Saves	-0.0967***	-0.0862***	-0.0763***
	(7.60)	(6.48)	(5.62)
Has access to cellphone	0.0107	-0.0259	-0.00992
	(0.79)	(1.93)	(0.67)
Owns bank account	-0.0989***	-0.0795***	-0.0729***
	(9.09)	(6.07)	(5.60)
N	12,411	12,411	12,411
R^2			

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression, the dependent variables being the dummies described in section 3.

Appendix 4: Results from Estimating Equation (1) for different Subsets of the sample

	Nutrition	Health	Education
	(1)	(2)	(3)
Full Sample (N = 12,411)	-0.0635***	-0.0339***	-0.0305**
Uses mobile money	(0.0109)	(0.0128)	(0.0124)
Cellphone Access only (N =9,927)	-0.0577***	-0.0290**	-0.0287**
Uses mobile money	(0.0111)	(0.0129)	(0.0126)
Rural Population only (N = 6,476)	-0.0707***	-0.0511***	-0.0452***
Uses mobile money	(0.014)	(0.0167)	(0.0166)
Financially excluded only (N = 9,667)	-0.0584***	-0.0340**	-0.0349***
Uses mobile money	(0.011)	(0.0134)	(0.0134)
Farming Population only (N = 9,902)	-0.0645***	-0.0283**	-0.0245*
Uses mobile money	(0.0115)	(0.0135)	(0.0133)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression, the dependent variables being the dummies described in section 3. Each regression contained the full set of controls detailed in section 4.

Appendix 5: Results from Estimating Equation (1) for each wealth quintile separately

	Nutrition	Health	Education
	(1)	(2)	(3)
Quintile 1 (N = 2453)	-0.0543***	-0.0562*	-0.0603**
Uses mobile money	(0.0205)	(0.0317)	(0.0304)
Quintile 2 (N = 2484)	-0.0629***	-0.0437*	-0.0464**
Uses mobile money	(0.0199)	(0.0235)	(0.0234)
Quintile 3 (N = 2489)	-0.0845***	-0.0335	-0.0500**
Uses mobile money	(0.0206)	(0.0246)	(0.0242)
Quintile 4 (N = 2491)	-0.0540*	-0.0144	-0.0019
Uses mobile money	(0.0277)	(0.0258)	(0.0272)
Quintile 5 (N = 2494)	-0.0393	-0.0095	0.0071
Uses mobile money	(0.0392)	(0.0351)	(0.0417)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression, the dependent variables being the dummies described in section 3. Each regression contained the full set of controls detailed in section 4.

Appendix 6: Results from using IPW and PSM to estimate the effect of Mobile Money

	Nutrition	Health	Education
	(1)	(2)	(3)
IPW: Uses mobile money	-0.0850***	-0.0517***	-0.0341**
	(0.0134)	(0.013)	(0.0137)
PSM: Uses mobile money	-0.0824***	-0.0387**	-0.0072
	(0.0169)	(0.0161)	(0.0183)
N	12,411	12,411	12,411

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression, the dependent variables being the dummies described in section 3. Matching was conducted on the full set of controls detailed in section 4.

A note on propensity score matching PSM: PSM is a method to obtain an average treatment effect (ATE), when treatment is not random. In propensity score matching, a logistic model is used to estimate each individual's propensity score of obtaining treatment, that is in my case using mobile money. For this purpose, individuals were matched on the full set of controls used when estimating equation 1. I used the default option, that is each non-treated subject was matched to one untreated subject who has the most similar propensity score.

Appendix 7: Correlations of control variables with health shock

Dependent Variable: Health Shock Indicator

	Full Sample	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)	(6)
Uses mobile money	0.007	-0.0011	0.0192	0.0012	0.0354	-0.0205
	(0.0122)	(0.0316)	(0.0237)	(0.0246)	(0.0263)	(0.0413)
Age	0.0031***	0.0022***	0.0017**	0.0045***	0.0043***	0.0031***
	(0.0003)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
Is female	0.0336***	0.0255	0.0553**	0.0164	0.0426**	0.0365*
	(0.0097)	(0.0257)	(0.0223)	(0.0221)	(0.0206)	(0.0199)
primary education	0.0199*	-0.0017	-0.0002	0.0145	-0.0204	0.0509**
	(0.0111)	(0.0232)	(0.0246)	(0.0283)	(0.0295)	(0.0253)
secondary education	0.0134	0.0813	0.0155	-0.0023	-0.0137	0.0187
	(0.0135)	(0.0498)	(0.0407)	(0.0348)	(0.0329)	(0.0222)
Is married	0.0151	0.0483*	0.0198	0.0331	-0.0159	-0.0233
	(0.0113)	(0.0263)	(0.0264)	(0.0251)	(0.0268)	(0.0243)
HH size	-0.0004	-0.0069	-0.008	0.0066	0.0056	-0.0016
	(0.0024)	(0.0059)	(0.0058)	(0.0053)	(0.0055)	(0.0048)
HH head is female	0.021	0.0237	-0.0128	0.0294	0.0285	0.0218
	(0.0135)	(0.0308)	(0.0322)	(0.0311)	(0.03)	(0.0267)
HH lives in urban area	-0.0048	0.0274	0.0012	-0.0229	-0.0157	-0.0201
	(0.013)	(0.0262)	(0.0262)	(0.0258)	(0.0248)	(0.0351)
HH is engaged in farming	-0.013	-0.0014	-0.0542	-0.0823**	-0.0628**	0.0008
	(0.012)	(0.0338)	(0.04)	(0.0371)	(0.0255)	(0.0194)
HH wealth quintile	-0.0207***					
	(0.0047)					
Travel time to nearest market	0.0143***	0.0242**	0.0025	0.0107	0.0149	0.01
	(0.0052)	(0.0109)	(0.011)	(0.0107)	(0.0106)	(0.0135)
Saves	0.0255*	0.019	0.0165	0.0257	0.0063	0.0993***
	(0.0133)	(0.023)	(0.0274)	(0.0315)	(0.0334)	(0.0374)
Has access to cellphone	0.0544***	0.0910***	0.0134	-0.0104	0.0241	0.1727***
	(0.0145)	(0.0234)	(0.027)	(0.034)	(0.0454)	(0.0595)
Owns bank account	-0.0311**	-0.0482	-0.0179	0.0213	-0.0086	-0.0307
	(0.0127)	(0.0658)	(0.0428)	(0.0314)	(0.0235)	(0.022)
N	12,411	2,453	2,484	2,489	2,491	2,494
R^2	0.021	0.019	0.008	0.025	0.025	0.021

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression run on the subsample detailed in the second row. The dependent variable is the health shock indicator.

Appendix 8: Correlations of control variables with health shock - rural and farming population only

Dependent Variable: Health Shock Indicator						
	Full Sample	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)	(6)
Uses mobile money	0.0112	0.0070	0.0197	0.0244	0.0147	-0.0432
	(0.0164)	(0.0369)	(0.0280)	(0.0310)	(0.0445)	(0.1052)
Age	0.0028***	0.0019**	0.0016*	0.0046***	0.0039***	0.0040
	(0.0005)	(0.0008)	(0.0009)	(0.0010)	(0.0013)	(0.0035)
Is female	0.0346**	0.0234	0.0600**	0.0044	0.0503	0.1306
	(0.0137)	(0.0299)	(0.0261)	(0.0268)	(0.0346)	(0.0794)
Completed primary education	-0.0149	-0.0255	-0.0109	0.0112	-0.0572	-0.0901
	(0.0163)	(0.0267)	(0.0304)	(0.0377)	(0.0463)	(0.1206)
Completed secondary education	0.0090	0.0716	0.0187	0.0299	-0.0374	-0.0902
	(0.0240)	(0.0595)	(0.0505)	(0.0466)	(0.0527)	(0.1194)
Is married	0.0246	0.0455	0.0211	0.0350	-0.0184	-0.0086
	(0.0169)	(0.0310)	(0.0320)	(0.0333)	(0.0474)	(0.1015)
HH size	-0.0032	-0.0161**	-0.0087	0.0052	0.0148	-0.0132
	(0.0036)	(0.0071)	(0.0071)	(0.0070)	(0.0091)	(0.0202)
HH head is female	0.0144	-0.0018	-0.0167	0.0789*	0.0267	0.0105
	(0.0203)	(0.0374)	(0.0396)	(0.0419)	(0.0560)	(0.1120)
HH wealth quintile	-0.0134*					
	(0.0069)					
Travel time to nearest market	0.0170**	0.0210	-0.0049	0.0190	0.0291*	0.0519
	(0.0073)	(0.0134)	(0.0140)	(0.0144)	(0.0161)	(0.0344)
Saves	0.0298	0.0390	0.0032	0.0365	0.0108	0.2472**
	(0.0184)	(0.0270)	(0.0351)	(0.0462)	(0.0647)	(0.1040)
Has access to cellphone	0.0518***	0.0891***	0.0193	-0.0214	0.0560	0.1454
	(0.0184)	(0.0269)	(0.0325)	(0.0451)	(0.0741)	(0.1675)
Owns bank account	-0.0020	-0.1094	0.0577	0.0332	0.0080	-0.0997
	(0.0235)	(0.0701)	(0.0571)	(0.0408)	(0.0430)	(0.0703)
N	6,070	1,778	1,700	1,497	902	193
R^2	0.015	0.023	0.009	0.027	0.026	0.079

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression run on the subsample detailed in the second row. The dependent variable is the health shock indicator.

Appendix 9: Correlations of control variables with weather shock

Dependent Variable: Weather Shock Indicator

	Full Sample	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(1)	(2)	(3)	(3)	(3)
Uses mobile money	0	-0.0507	0.0363	0.0161	-0.0071	-0.0265
	(0.0141)	(0.0334)	(0.0265)	(0.0238)	(0.0256)	(0.0336)
Age	0.0004	-0.0004	0.0001	0.0012	0.0007	0.0007
	(0.0004)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
Is female	-0.0021	0.0365	0.0117	-0.0135	-0.0019	-0.0378***
	(0.0093)	(0.0257)	(0.0222)	(0.0198)	(0.0188)	(0.0143)
primary education	0.0174	0.0225	-0.0203	0.0442	0.0479*	-0.0183
	(0.0123)	(0.0255)	(0.0257)	(0.0279)	(0.0258)	(0.0229)
secondary education	0.0152	0.0298	0.0096	0.0127	0.0445	0.0033
	(0.0142)	(0.0537)	(0.0395)	(0.0363)	(0.0314)	(0.0181)
Is married	0.0064	-0.0277	-0.0121	0.0221	-0.0015	0.0548**
	(0.0117)	(0.0259)	(0.0255)	(0.0257)	(0.0236)	(0.022)
HH size	0.0029	0.0012	-0.0026	0.0067	0.0048	0.0014
	(0.0027)	(0.0059)	(0.0064)	(0.0055)	(0.0047)	(0.0038)
HH head is female	-0.0067	-0.0737**	-0.0259	0.0199	-0.0064	0.0533**
	(0.0129)	(0.0305)	(0.0292)	(0.0296)	(0.0264)	(0.0242)
HH lives in urban area	-0.0861**	-0.0822	-0.1301***	-0.1217***	-0.0571	0.003
	(0.0377)	(0.0509)	(0.0469)	(0.0448)	(0.0435)	(0.0515)
HH is engaged in farming	0.0830***	0.0788**	0.0558	0.0252	0.1045***	0.0999***
	(0.0177)	(0.0363)	(0.0413)	(0.038)	(0.0275)	(0.0236)
HH wealth quintile	-0.0351***					
	(0.0072)					
Travel time to nearest market	0.0348***	0.0411**	0.0310*	0.0193	0.0411***	0.0479***
	(0.0114)	(0.0163)	(0.0158)	(0.0156)	(0.0147)	(0.0169)
Saves	0.0441***	0.0902***	0.0308	0.0246	0.0166	-0.0205
	(0.0164)	(0.0263)	(0.03)	(0.03)	(0.0366)	(0.0362)
Has access to cellphone	0.0450***	0.0613**	0.0157	0.0305	0.0732*	0.0859
	(0.0156)	(0.0263)	(0.0273)	(0.0313)	(0.0416)	(0.0623)
Owns bank account	-0.0023	0.0628	-0.0456	0.0438	0.0061	-0.0393**
	(0.0147)	(0.0788)	(0.0406)	(0.0329)	(0.0244)	(0.0192)
N	12,411	2,453	2,484	2,489	2,491	2,494
R^2	0.031	0.04	0.031	0.032	0.043	0.045

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression run on the subsample detailed in the second row. The dependent variable is the weather shock indicator.

Appendix 10: Correlations of control variables with weather shock - rural and farming population only

Dependent Variable: Weather Shock Indicator

	Full Sample	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(1)	(2)	(3)	(3)	(3)
Uses mobile money	0.009	-0.0549	0.0537	0.0354	-0.027	0.0431
	(0.0207)	(0.0407)	(0.0328)	(0.0329)	(0.0426)	(0.1036)
Age	0	-0.0007	-0.0002	0.0007	0.0004	0.0028
	(0.0006)	(0.0009)	(0.001)	(0.0011)	(0.0013)	(0.0029)
Is female	0.0085	0.0333	0.0004	0.0042	0.0167	-0.0978
	(0.0146)	(0.0309)	(0.0268)	(0.0259)	(0.0339)	(0.0675)
Completed primary education	0.016	0.0158	-0.0175	0.0176	0.0724	-0.1582
	(0.0201)	(0.0309)	(0.0332)	(0.0384)	(0.0477)	(0.0997)
Completed secondary education	0.0123	0.0423	0.0187	-0.0408	0.0806	-0.0583
	(0.027)	(0.0628)	(0.0491)	(0.0498)	(0.0596)	(0.0942)
Is married	-0.0026	-0.0318	0.001	0.0062	0.0194	0.1105
	(0.0177)	(0.0309)	(0.0326)	(0.0363)	(0.043)	(0.1112)
HH size	0.0051	0.0032	-0.0036	0.0106	0.0055	0.0376**
	(0.0042)	(0.0071)	(0.0079)	(0.007)	(0.0092)	(0.0174)
HH head is female	-0.0287	-0.0765**	-0.0304	0.0161	-0.0302	0.2144
	(0.0212)	(0.0383)	(0.0372)	(0.0444)	(0.0543)	(0.1326)
HH wealth quintile	-0.0451***					
	(0.0108)					
Travel time to nearest market	0.0402**	0.0465**	0.0422**	0.0154	0.0491**	0.0413
	(0.0161)	(0.0203)	(0.0197)	(0.0211)	(0.0242)	(0.0376)
Saves	0.0679***	0.1217***	0.023	0.0379	0.0267	-0.1372
	(0.0242)	(0.0336)	(0.0395)	(0.0478)	(0.0724)	(0.1757)
Has access to cellphone	0.0255	0.0428	0.0105	-0.0094	0.0346	0.1885
	(0.0207)	(0.0306)	(0.0342)	(0.0439)	(0.0704)	(0.136)
Owns bank account	0.0294	0.0567	-0.0914*	0.1069**	0.0549	-0.0749
	(0.0292)	(0.0952)	(0.0526)	(0.0448)	(0.0472)	(0.067)
N	6,070	1,778	1,700	1,497	902	193
R^2	0.019	0.027	0.012	0.011	0.021	0.091

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column refers to a separate regression run on the subsample detailed in the second row. The dependent variable is the weather shock indicator.

Appendix 11: Results from estimating equation (2) for each shock measure separately for the full sample and for each wealth quintile

	Dependent variable: Received remittances dummy											
	Full Sample		Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Mobile Money	0.3340***	0.3342***	0.2577***	0.2252***	0.2955***	0.3039***	0.3339***	0.3231***	0.3810***	0.3783***	0.4121***	0.3956***
	(0.0108)	(0.0111)	(0.0318)	(0.0285)	(0.0242)	(0.0236)	(0.0222)	(0.0204)	(0.0223)	(0.0231)	(0.0365)	(0.0357)
Mobile Money x Healthshock	0.0199		0.0789		0.0500		0.0112		0.0364		-0.0661	
	(0.0142)		(0.048)		(0.0349)		(0.032)		(0.0333)		(0.0613)	
Healthshock	0.0198***	0.0014		0.0382***	0.0091		0.0213		0.0790			
	(0.0071)		(0.0099)		(0.0145)		(0.017)		(0.0244)		(0.057)	
Mobile Money x Weathershock		0.0238		0.1664***	0.033		0.0414		0.0660*		-0.0317	
		(0.0169)		(0.0461)		(0.0346)		(0.0352)		(0.0373)		(0.0723)
Weathershock		0.0155**		0.0114		-0.007		0.0397**		-0.0382		0.0411
		(0.0076)		(0.0103)		(0.0143)		(0.0191)		(0.025)		(0.0667)
N	12,411	12,411	2,453	2,453	2,484	2,484	2,489	2,489	2,491	2,491	2,494	2,494
R^2	0.22	0.218	0.18	0.19	0.18	0.177	0.16	0.161	0.15	0.149	0.07	0.07

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each Regression included the vector of control variables, these coefficients are not reported for clarity.

Appendix 12: Results from estimating equation (2) using the health shock and considering the rural and farming population only

	Dependent variable: Received remittances dummy					
	Full Sample (1)	Quintile 1 (2)	Quintile 2 (3)	Quintile 3 (4)	Quintile 4 (5)	Quintile 5 (6)
Mobile Money	0.3049*** (0.0148)	0.2502*** (0.0349)	0.2883*** (0.0302)	0.3040*** (0.0272)	0.3897*** (0.0362)	0.2207* (0.1142)
Mobile Money x Weathershock	0.0414* (0.0233)	0.1214** (0.0538)	0.0393 (0.0417)	0.0636 (0.0446)	0.0335 (0.055)	-0.3964 (0.2713)
Weathershock	0.0131 (0.0087)	0.0079 (0.0109)	0.0052 (0.0174)	0.0452* (0.0232)	-0.0464 (0.0341)	0.3571 (0.2512)
N	6,070	1,778	1,700	1,497	902	193
R^2	0.20	0.20	0.17	0.16	0.16	0.13

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each Regression included the vector of control variables, these coefficients are not reported for clarity.

Appendix 13: Results from estimating equation (2) using the weather shock measure and considering the rural and farming population only.

	Dependent variable: Received remittances dummy					
	Full Sample (1)	Quintile 1 (2)	Quintile 2 (3)	Quintile 3 (4)	Quintile 4 (5)	Quintile 5 (6)
Mobile Money	0.3062*** (0.0148)	0.2532*** (0.0367)	0.2913*** (0.0302)	0.3276*** (0.0296)	0.3777*** (0.0345)	0.1359 (0.1254)
Mobile Money x Healthshock	0.0376* (0.0212)	0.1097** (0.0558)	0.0371 (0.0428)	0.0098 (0.0417)	0.0571 (0.0518)	-0.0365 (0.1834)
Healthshock	0.0097 (0.0082)	-0.0022 (0.0108)	0.0324* (0.0178)	0.0019 (0.0218)	0.0223 (0.035)	-0.0364 (0.182)
N	6,070	1,778	1,700	1,497	902	193
R^2	0.20	0.20	0.17	0.15	0.16	0.12

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Each Regression included the vector of control variables, these coefficients are not reported for clarity.

Appendix 14: Spending profile of remittances sent via mobile money

	Full Sample	Wealth Quintile 1	Wealth Quintile 2	Wealth Quintile 3	Wealth Quintile 4	Wealth Quintile 5
Investment	5.83%	3.33%	3.89%	6.29%	6.36%	6.32%
Business	5.96%	0.56%	1.60%	4.68%	7.02%	8.39%
Bought food/clothes	54.50%	63.33%	61.33%	54.52%	53.51%	51.17%
Paid school fees	8.93%	5.56%	3.89%	6.61%	9.65%	12.18%
Paid medical fees/medicine	9.49%	12.78%	15.10%	10.00%	8.88%	6.95%
Paid funeral expenses	0.92%	0.56%	1.14%	1.29%	0.77%	0.81%
Buying or building a house	2.76%	4.44%	2.06%	3.23%	2.63%	2.62%
Renting a house	1.47%	0.56%	0.23%	0.97%	1.64%	2.26%
Other, specify	10.13%	8.89%	10.76%	12.42%	9.54%	9.30%

Appendix 15: Frequency of remittances-sending by mobile money usage status

	Users of Mobile Money	Non-Users of Mobile Money
Weekly	3.48%	3.45%
Fortnightly	5.98%	0.77%
Monthly	15.19%	9.20%
Seasonally	10.24%	9.58%
Once a year	5.00%	4.60%
Irregularly/occasionally	60.11%	72.41%